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ECONOMIC DEVELOPMENT AND LOSSES DUE TO NATURAL DISASTERS: THE ROLE OF RISK

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***Abstract*:** We show that the relationship between wealth and economic losses due to natural disasters is strongly linked to disaster risk. We first build an analytical model that demonstrates how countries that face a low hazard of disasters are likely to see first increasing losses and then decreasing ones with increasing economic development. At the same time, countries that face a high hazard of disasters are likely to experience first decreasing losses and then increasing ones with increasing economic development. We then use a cross country panel dataset in conjunction with a risk exposure index to investigate whether the data is consistent with the predictions from the model. As suggested by our model, we generally find an inverse u-shaped link between losses and wealth for low and medium hazard countries, but a u-shaped relationship for high hazard countries.

Key Words : Economic development, disasters, risk, uncertainty, hazard index

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1. Introduction

There are certainly few issues more disturbing than the prospect of losing one's hard-earned belongings to the forces of nature. One single instant of a wave, a tremble of the earth, or a passing by of a hurricane is often enough to destroy one's house, one's work, and one's belongings, if not one's life. Unfortunately, from a global perspective such events are less infrequent than one might imagine. Abundant news coverage shows us pictures from flooded houses in New Orleans, hurricane-torn houses in Burma, dried fields in Sub-Saharan Africa and earthquake damages in Chengdu in China. For example, in 2007 alone there were approximately 450 of these natural disasters worldwide, affecting around 211 million people, and causing economic losses amounting to 74 billion US dollars.[2]

One of the main stylized facts that has arisen from the still relatively new academic literature on natural disasters seems to be that the economic and human losses associated with natural disasters are larger the poorer a country is.[3] This was first shown by Tol and Leek (1999) and Burton et al (1993) for a sample of 20 nations and later confirmed in more comprehensive studies covering a large panel of countries by Kahn (2005) and Toya and Skidmore (2007). Yet, surprisingly, beyond arguing, for example, that "as a country develops, it devotes greater resources to safety, including precautionary measures…" (Hideki and Skidmore, p. 20) there is, to our knowledge, no study investigating the underlying mechanics driving this link, either of an empirical or of a theoretical nature.[4, 5]

[2] Most of these costs are due to storm damages, floods and earthquakes (EM-DAT database).

[3] For example, Anbarci et al (2005) note that to "say that the level of fatalities resulting from an earthquake is inversely related to a country's per capita level of income is hardly novel" (p. 1907).

[4] Kahn (2005) and Toya and Skidmore (2007) do examine what county characteristics (e.g., education, quality of institutions, etc.) are correlated with the relationship between economic development and disaster losses, but only in an ad hoc manner.

Arguably a key element in understanding how losses from natural disasters are related to income is the expected risk of these events. More specifically, Toya and Skidmore (2007) note that there are two relevant components to the disaster-income relationship, namely, (1) increases in income increase the demand for safety, and (2) higher income enables individuals to employ costly precautionary measures in response to this demand. So, if two countries face the same level of risk one should expect the one with higher income to spend more on precautionary measures and hence to suffer fewer losses if a natural disaster occurs. Similarly, given two countries with equal wealth one would expect the one with a higher risk to have a higher demand for reducing the exposure to this risk via precautionary measures. Thus, of two equally wealthy countries one should expect the one with less risk to suffer greater losses in the case of a natural disaster because it is likely to have invested less in precautionary measures.

Of course, as it is with wealth, the risk of natural disasters occurring is not evenly distributed across the globe. For instance, tropical cyclones are generally prevelant only in certain coastal areas (ex: US North Atlantic and Gulf Mexico coastline, Caribbean Sea, South Pacific etc.), while major earthquakes are likely to occur in locations where tectonic plates collide (ex: US, Turkey, Chile, etc.). Hence it seems reasonable to assume that the cross-country losses-income relationship is likely to depend on the (expected) risk of natural disasters that

[5] While there is a literature that deals with decision-taking under uncertainty and prevention, it has generally not specifically addressed natural disasters. The two main exceptions in this regard are the articles by Lewis and Nickerson (1992) , which deals with the amount of self-insurance under uncertainty, as well as Anbarci et al. (2005) , which relates inequality and collective action to self-insurance within a natural disaster context.

nations face.[6] In other words, if the difference in risk is large enough a low risk rich country may very well suffer larger losses than a poorer, but higher risk, country.[7]

In this paper we thus set out to explicitly investigate how this interplay between wealth and risk affects the manner in which natural disaster losses depend on the level of economic development. We first develop a theoretical model where agents choose their optimal level of adaptation under uncertainty. This uncertainty comes from two sources which together make up the natural hazard risk exposure that a country faces: One, the probability of a disaster; two, the uncertainty of the strength of a disaster, which is described by a probability density function. We analyze the implications of both sources of uncertainty as well as the state of economic development on the potential losses from disasters. This model helps us in providing an understanding of the driving mechanisms behind the relationship between the economic losses, the natural hazard risk exposure and economic development.

We next investigate whether our panel data is consistent with the predictions of our model. To this end we construct a proxy of country level risk exposure based on local (within) risk measures developed by Diley et al.(2005). We then use this index to explore the role differences in risk exposure play in the possibly non-linear income-losses relationship, as suggested by our theoretical model. Our econometric analysis demonstrates not only that the link between wealth and losses is non-linear, but that the shape of this relationship crucially depends on the risk of natural disasters faced by countries. More precisely, we generally find an inverse u-shaped link between losses and wealth for low and medium hazard countries, but

[6] Neither Toya and Skidmore (2007) nor Kahn (2005) explicitly take account of expected risk in this regard.

[7] More precisely, Toya and Skidmore (2007) regress losses on income on a sample of natural disasters without controlling for differences in risk, while Kahn (2005) controls only for the probability of the natural disaster event actually occurring (and not its expected risk).

a u-shaped relationship for high hazard countries. These results are robust to implementing alternative methodological approaches previously used in the literature.

The remainder of the paper is organized as follows. In the following section we outline our theoretical framework and its implications. In Section III we describe our data set. Our econometric specification and results are contained in Section IV. The final section concludes.

2. Theoretical Model

Our model follows in the spirit of Meyer and Ormiston (1989) and Lewis and Nickerson (1989), who basically analyze the optimal amount of adaptation expenditure if an uncertain amount of losses can be incurred. However, our main differences to their approach are in the definition of a disaster and the way a disaster transcendences into economic losses. We assume here that the amount of wealth destroyed depends on the amount of wealth available. Also, we assume that a disaster may or may not occur and, if it occurs, then the strength of the disaster is uncertain but given by a certain density function. Our agent then solves an expected utility problem where a disaster may occur with a probability $p \in (0,1)$ which reduces his wealth $W > 0$ by a percentage $1-\psi(x,y) \in (0,1)$. The function $\psi(x,y) \in (0,1)$ is a decreasing function of a random variable y but an increasing, concave function of the adaptation expenditure $x \geq 0$. The cost associated with x is given by the constant $c > 0$. The random variable y is defined by a cumulative distribution function $F(y)$ with support in the (normalized) interval $[0,1]$. A $y = 0$ then constitutes the best, a $y = 1$ the worst outcome. Economic losses are defined by $L \equiv W(1-\psi(x,y)) > 0$. When we refer to the risk exposure then we mean the combined effect of *p* and *y*. If both are low we will have a low risk exposure, for both high a high hazard, any other combination will lie between these two. The maximization problem then becomes

$$\max_x EU = (1-p)u(W-cx) + p\int_0^1 u(W\psi(x,y)-cx)dF(y), \quad (1)$$

subject to $x \geq 0$, where we assume that $I = W\psi(x,y) - cx \geq 0$ for all *y* and feasible *x*. We shall denote the first derivative of the utility function by $u' > 0$, the second and third derivate by $u'' < 0$ and u''', respectively. The derivative of any other function is denoted by a subscript with the variable in question. Most of our results are still valid if we were to allow for different utility functions in case there is a disaster and in case there is none. For simplicity though we assume both utility functions to be the same.

The first-order condition of the above maximization problem is

$$\Omega \equiv -(1-p)u'c + p\int_0^1 u'\{W\psi_x - c\}dF(y) \leq 0, \quad (2)$$

with equality for $x > 0$. The Kuhn-Tucker complementary slackness condition is $\Omega x = 0$.

The second-order condition for this problem is given by

$$(1-p)u''c^2 + p\int_0^1 (u''\{W\psi_x - c\}^2 + u'W\psi_{xx})dF(y) < 0, \quad (3)$$

due to the concave utility function and since $\psi_{xx} < 0$.

At an interior solution s.th. $x > 0$ we have $W\psi_x > c$ (condition A). Condition A, which is a necessary but not a sufficient condition for an interior *x*, will be satisfied for a small enough c, large enough W and if the marginal effectiveness from adaptation expenditure is sufficiently large for any *x*. We shall see that this condition plays a crucial role for the subsequent analysis.

Our intention now is to study how some parameters of interest, namely *p*, *W*, *y* affect the optimal amount of adaptation expenditure and the amount of economic losses. We are particularly interested in possible corner solutions and in how adaptation expenditure changes with changes in these parameters. Our main emphasis though will be on changes in wealth, since we wish to track the size of the economic losses along different stages of economic development.

In the remainder of this article we may sometimes impose the following assumptions.

(A0) The utility function in case of a disaster has constant relative risk aversion (CRRA), such that $\sigma = -\frac{I u''}{u'}$, where $\sigma > 0$.

(A1) $\lim_{W \to 0} u' = \mathrm{M}$, where $M < \infty$.

(A2) $\lim_{x \to 0} \psi_x(x, y) < \infty$, $\forall y$.

Assumption (A0) is widely used and implies prudence ($u''' > 0$). Assumption (A1) states that marginal utility is bounded above by a positive, finite number. Assumption (A2) suggests that the returns to an investment in adaptation expenditure are finite for any *x*, an assumption which does not seem to strong.

Case 1: corner solution

We shall now study the conditions under which a corner solution in adaptation expenditure may occur. This we do for the parameters *p*, *y* and *W*.

<u>Proposition 1</u>: *Economic losses from disasters are increasing for* $W \in [0, \widetilde{W}]$ *if the risk exposure is small enough or if assumptions (A1) and (A2) are satisfied.*

Firstly, $x = 0$ if

$$\frac{1}{p} > \frac{cu' + \int_0^1 u'\{W\psi_x - c\} dF(y)}{cu'}, \tag{4}$$

which holds for *p* small enough. Therefore, ceteris paribus, the smaller the probability of a disaster the more likely the agent will not undertake any adaptation expenditure. In the limit, if $p \to 1$, then a sufficient condition for positive adaptation expenditure is $W\psi_x \geq c$. Therefore, increases in *p* are more likely to lead to interior solutions of *x* and weaken condition A.

Secondly, at the optimum, we know $\exists \beta \in (0,1)$ such that $u'(I^\beta)\{W\psi_x(x(\beta),\beta) - c\} = \int_0^1 u'(I)\{W\psi_x(x,y) - c\}dF(y)$, for given *x* and a given distribution of *y*, where $I^\beta = W\psi(x(\beta),\beta) - cx(\beta)$. Thus, there will be no adaptation expenditure if

$$u'(I^\beta)W\psi_x(x,\beta) < \frac{(1-p)}{p}u'c + cu'(I^\beta). \quad (5)$$

The right-hand side of this inequality describes the combined marginal cost of adaptation expenditure in both the good and average bad state, whereas the left-hand side describes the marginal benefit of adaptation expenditure in case of an average disaster. The question would now be how this marginal loss changes with increases in the average strength of the disaster (i.e. an increase in β). In case of a corner solution, where $x = 0$, the right-hand side, i.e., marginal costs, are strictly increasing in β. The left-hand side changes with changes in β according to $u''W^2\psi_x(x,\beta)\psi_y(x,\beta) + u'W\psi_{xy}(x,\beta)$, which is positive if $\psi_{xy} > 0$ but bears an ambiguous sign if $\psi_{xy} < 0$. The left-hand side increases faster in *y* than the right-hand side if

$$\frac{\psi_{xy}}{\psi_y} < -\frac{I^\beta u''}{u'}\frac{(W\psi_x - c)}{I^\beta}. \quad \text{(condition B)}$$

Therefore, starting from a corner solution, a higher average strength of disasters leads to an interior solution in adaptation expenditure only if condition B is satisfied. Condition B relates risk aversion when a disaster occurs to the relative effectiveness and net wealth effect of adaptation expenditure for a given marginal change in the strength of a disaster. Since adaptation is less efficient for larger disasters if $\psi_{xy} < 0$, an increase in risk will increase adaptation expenditure only if risk aversion is large enough, if wealth is sufficiently large or the costs very low. However, one would more likely expect natural disasters to fall in the category of risks which have $\psi_{xy} > 0$. This is the case for disasters like earthquakes, hurricanes or floods. For weak earthquakes, weak hurricanes, or minor floods one would expect that the marginal benefit of adaptation expenditure is rather small. However, for strong earthquakes the skyscrapers on hydraulic balances in Japan or for big floods the damns in Netherlands provide huge marginal benefits. In that case, $dx/d\beta > 0$. Therefore, countries that are subject to a higher risk will also invest more in adaptation expenditure.

Thirdly, if we impose (A1) as well as (A2), then from the first-order conditions we obtain

$$\lim_{W \to 0} \left\{ -(1-p)u'c + p\int_0^1 u'\{W\psi_x - c\}dF(y) \leq 0 \right\} \quad \Rightarrow \quad -cM < 0. \tag{6}$$

Thus, there will be no adaptation expenditure for small enough wealth if assumptions (A1) and (A2) are satisfied. If either of the two conditions is not satisfied, then it is possible that even for small wealth, agents will undertake a positive amount of adaptation if it proves to be sufficiently effective.

Rewriting the first-order condition for the case of a corner solution gives us

$$\int_0^1 u'W\psi_x dF(y) < c(1/p-1)u' + c\int_0^1 u'dF(y). \tag{7}$$

The left-hand side describes the marginal benefits from adaptation expenditure, whereas the right-hand side describes the total marginal costs of adaptation expenditure across the good and the bad state. Marginal benefits decline slower than marginal costs if

$$p\int_0^1 (u''\psi(W\psi_x - c) + u'\psi_x)dF(y) > (1-p)u''c\,. \qquad \text{(condition C2)}$$

Condition C2 is a necessary condition for increasing wealth to lead to an interior solution in *x*. If either of the two conditions is satisfied then $\exists\widetilde{W} > 0$, such that $\lim_{W\uparrow\widetilde{W}} \Omega(W) = 0$. Therefore, starting from a corner solution in adaptation expenditure, increases in wealth lead to an interior solution for adaptation expenditure only if condition C2 is satisfied. This result is closely linked to the one under optimal prevention, see, e.g., Eeckhoudt and Gollier (2005). We thus find that for low levels of wealth, adaptation expenditure may be zero. If wealth increases, then condition C2 is necessary and sufficient for the existence of a level of wealth which leads to an interior solution in *x*.

As shown above, corner solutions are more likely to occur the lower the exogenous probability of a disaster, the lower the wealth, the lower the costs of adaptation expenditure and the lower the average strength of a disaster. Thus, smaller natural hazard levels imply lower expenditures on adaptation. Economic losses are then clearly increasing in the case of corner solutions, denoted by L^c. Since economic losses in case of a corner solution are given by $L^c = W(1-\psi(0,y))$, we can easily show that economic losses increase with increases in *y* and W. Indeed, we have that $\frac{dL^c}{d\beta} = -W\psi_y(0,\beta) > 0$ and $\frac{dL^c}{dW} = 1-\psi(0,y) > 0$. Though actual losses are independent of *p* in case of a corner solution, the expected losses, defined as pL^c, are an increasing function of the probability of a disaster.

Case 2: interior solution

Here we shall study the economic losses for the interior solution in *x*.

Proposition 2: *A higher frequency of disasters leads to a larger adaptation expenditure, whereas stronger disasters require a high enough and higher wealth requires a small enough risk aversion for increasing adaptation expenditure. Economic losses may then increase or decrease with increasing wealth.*

The effect of an increase in *p* for the case of an interior solution is given by

$$\frac{dx}{dp} = -\frac{cu' + \int_0^1 u'\{W\psi_x - c\}dF(y)}{(1-p)u''c^2 + p\int_0^1 (u''\{W\psi_x + c\}^2 + u'W\psi_{xx})dF(y)} > 0. \tag{8}$$

The denominator is negative due to the concavity of the optimization problem and the nominator is positive for $x > 0$. Therefore, a higher probability of a disaster leads to an increase in the adaptation measures in order to reduce the effect of a disaster on wealth. Thus, in case of an interior solution, countries which face a higher probability of being hit by a disaster should see more adaptation expenditure for a given level of wealth.

We shall now analyze the case of an increase in risk as defined by Meyer and Ormiston (1989). We use a deterministic transformation of risk, defined as $k(y) \equiv \phi(y) - y$, where the following two conditions need to be satisfied: 1) $\int_0^1 k(y)dF(y) = 0$ and 2) $\int_0^g k(y)dF(y) \leq (\geq) 0$, $\forall g \in [0,1]$. Condition (1) implies that the mean of *y* is unchanged whereas condition 2) guarantees that *y* SOSD (is SOSDed by) the transformed random variable if there is an increase (decrease) in risk. For simplicity we assume $k(y) > 0$, which is a special case of Condition (2). Our optimization problem, given the transformation, then changes to:

$$\max_x EU = (1-p)u(W-cx) + p\int_0^1 u(W\psi(x, y+\gamma\phi(y)) - cx)dF(y)\,. \tag{9}$$

In this case we can directly show that expected utility is reduced if there is an increase in risk as represented by a change in γ. Mathematically, this is given by

$$\frac{dEU}{d\gamma} = -p\int_0^1 u'W\psi_y\phi(y)dF(y) < 0\,. \tag{10}$$

The first-order conditions are equivalent to above. Increases in risk then imply that the control variable changes according to

$$\frac{dx}{d\gamma} = -\frac{p\int_0^1 (u''\{W\psi_x - c\}\psi_y + u'\psi_{xy})W\phi(y)dF(y)}{(1-p)u''c^2 + p\int_0^1 (u''\{W\psi_x - c\}^2 + u'W\psi_{xx})dF(y)}\,. \tag{11}$$

For $\psi_{xy} > 0$ we get $dx/d\gamma > 0$, whereas for $\psi_{xy} < 0$ we obtain an indeterminate sign. The sign of ψ_{xy} depends crucially on the underlying interpretation. If ψ_{xy} is positive, then the marginal effect of adaptation is larger the stronger the disasters. If the marginal effect of adaptation is decreasing in the strength of the disaster, such that $\psi_{xy} < 0$, then $dx/d\gamma > 0$ if

$$-\frac{I\,u''}{u'} > \frac{\psi_{xy}}{\psi_y}\frac{I}{(W\psi_x + c)}\,. \tag{condition B'}$$

The interpretation of condition B' is analogous to that of condition B.

Similarly, we can calculate the effect of an increase in *W* on the amount of adaptation expenditure undertaken. We find that for a given probability of a disaster, we get

$$\frac{dx}{dW} = \frac{(1-p)cu'' - p\int_0^1 (u''\{W\psi_x - c\}\psi + u'\psi_x)dF(y)}{(1-p)u''c^2 + p\int_0^1 (u''\{W\psi_x - c\}^2 + u'W\psi_{xx})dF(y)}, \tag{12}$$

for an interior *x*. Just like before the denominator is negative by the concavity of the optimization problem, while the nominator may be positive or negative. A sufficient condition for $\frac{dx}{dW} > 0$ is

$$-\frac{Iu''}{u'} < \frac{\psi_x}{\psi}\frac{I}{(W\psi_x - c)}, \quad \text{(condition D)}$$

where *I* is the net wealth after damages. Assuming (A0), then condition D is more likely to be satisfied if risk aversion is small, if adaptation expenditure is effective, if the percent of wealth destroyed in case of a disaster is large and if net wealth is high. Indeed, what this condition suggests is that agents with high risk aversion are likely to spend relatively more money on adaptation expenditure if poor rather than rich. Intuitively, higher risk aversion increases the marginal value of wealth, thereby reducing incentives to invest in adaptation. Only if enough risk can be transferred from a high y state to a low y state (via e.g. a high marginal effectiveness of x) will increasing wealth increase adaptation expenditure.

Finally, it could very well be that $\frac{dx}{dW} \leq 0$, especially if the marginal returns to adaptation expenditure are decreasing quickly enough. While we suggested above that $\psi_{xy} > 0$ is likely to hold for the case of disasters, it is also quite likely that $\psi_{xx} < 0$ is large. This would for example be the case for threshold effects in disasters. Though it might be possible to protect oneself from floods via sufficiently high damns, it is rather unlikely to build damns high enough to stop tsunamis. Or, while it might be possible to build irrigation systems to green the desert in Africa, these systems will be pretty useless in very dry years when even the Nile barely carries any water. In that case we can see from equation (12) that $\frac{dx}{dW} \le 0$ since $(1-p)cu'' < p\int (u''\{W\psi_x - c\}\psi + u'\psi_x)dF(y)$ is more likely the smaller is ψ_x.

Economic losses in case of an interior solution, denoted by L^i, are given by $L^i = W(1-\psi(x,y))$. A higher exogenous probability of a disaster leads to $\frac{dL^i}{dp} = -W\psi_x \frac{dx}{dp} < 0$. Therefore, countries which have a higher probability of a disaster will have lower economic losses. However, expected losses may increase or decrease. They decrease if the percent of wealth destroyed is low, if the probability of a disaster is high and if adaptation expenditure is very effective. Economic losses are also responsive to differences in risk. A higher risk leads to $\frac{dL^i}{d\gamma} = -(\psi_y \phi(y) + \psi_x \frac{dx}{d\gamma})W$. Therefore, countries that face a larger exogenous risk of having to bear strong disasters will only see a decline in economic losses if $\psi_{xy} > 0$ or if $\psi_{xy} < 0$ plus condition B' holds, and if the marginal effectiveness of adaptation expenditure is sufficiently strong. Therefore, speaking in terms of a combined natural hazard index, countries with a higher hazard index are likely to see lower economic losses than those with a low hazard index if the marginal effectiveness of adaptation expenditure is sufficiently strong.

Finally, increases in wealth only lead to a reduction in economic losses if $\frac{dL^i}{dW} = (1-\psi) - W\psi_x \frac{dx}{dW} < 0$. Increases in wealth then may increase the amount of wealth spend on adaptation expenditure if condition A is satisfied. This may therefore lead to an overall reduction in economic losses along the economic development. However, if after a certain level of adaptation the marginal returns to adaptation expenditure are sufficiently decreasing, then it is likely that adaptation expenditure will be reduced, which leads to increasing losses from increasing wealth again.

In summary, we can state the following broad conclusions. Countries which have a low probability of being hit by a disaster are likely to see higher economic losses than countries which have a high probability of being hit by a disaster. Countries which have more low-strength disasters will see higher economic losses than high-strength disaster countries if a) adaptation expenditure becomes increasingly effective for high-strength disasters; or if b) risk aversion is high enough. Countries that face a low risk exposure are likely to see economic losses increase with increasing wealth. However, in case of a low enough marginal value of wealth, sufficiently effective adaptation expenditure, high enough fraction of wealth that is destroyed and high enough net wealth, then there exists a level of wealth which leads to increasing adaptation expenditure with increasing wealth and therefore diminishing losses. This suggests a possible non-linearity in the relationship between economic losses and the stage of economic development and points at the importance of the hazard risk exposure.

3. Data

3.1 Risk exposure Data

An important aspect of our study with regard to investigating whether the data are consistent with predictions of our theoretical model is a proxy for the expected risk of a natural disaster. From an empirical perspective ideally one would thus like to have some sort of indicator of the probability density function for natural disaster which describes the probability of occurrence along the complete range of intensities. In order to derive such a proxy we avail of the natural disaster global hot-spots data constructed by a joint effort from the World Bank Hazard Management Unit and the Center for Hazards and Risks Research Unit at Columbia University; see Diley et al (2005). More specifically, this research team developed a innovative summary proxy of risk exposures faced locally (within countries) across the globe, that takes account of both the likelihood of a natural disaster event as well as the local exposure (in terms of population) to it for five different natural disasters: cyclones, earthquakes, landslides, floods, and droughts. Details of their methodology underlying the construction of their multi-hazard indicator is given in the Data Appendix.

As outlined in the Data Appendix, the multi-hazard index by Diley et al (2005) is calculated for local sub-national level grid cells. In order to arrive at a national measure of natural disaster (per capita) hazard, we summed grid cells' multi-hazard values within countries and normalize this sum by a country's population size (in '000s) in 2000 as given by the GPW data.[8] We depict our country level proxy of natural disaster hazard in Figure 1. The graph demonstrates the unequal distribution of risk exposure across the globe. Although not easily detectable from the graph, the highest hazard countries are, unsurprisingly, mostly small islands – as, for example, Vanuata, Turks and Caicos Islands, Belize etc. – although also some larger countries also feature in the very hazardous groups (ex: Somalia, Afghanistan, Chile, etc.).

[8] One may want to note that we use the population size in 2000 since the population density data weighting scheme of our measure is also derived from 2000 data.

3.2 Economic Loss Data

The loss due to natural disasters data that we use are compiled from the now well-known EM-DAT database[9] maintained by the Centre for Research on the Epidemology of Disasters (CRED) which compiles information on natural disasters across countries over time, where natural disasters are defined as natural events that overwhelm local capacity, necessitating a request for assistance from national or international levels. The information underlying the data is derived from a variety of sources, including international and research institutions, insurance companies, and press agencies. In order for an event to be considered a natural 'disaster' it must report having caused deaths of at least ten people, having affected at least 100 people, resulted in a call for international assistance, and/or resulted in a declaration of a state of emergency. Given the definition of our multi-hazard measure we limit our analysis to economic losses due to windstorms, droughts, earthquakes, floods, landslides, and volcanoes as defined by the EM-DAT database. The average yearly per capita losses are depicted in Figure 2.[10] Accordingly, even within continents there are notable differences in the economic losses due to natural disasters. If one examines the group of countries with the greatest losses, one discovers that this includes both developed (ex: US, Japan, etc.) as well as developing nations (ex: Philippines, Mexico, etc.).

3.4 Other Data

Our time varying country level measure of GDP per capita is taken from the World Penn Data Tables. Additionally, we use its estimate of population size by country over time. Finally,

[9] For recent uses of this data see, for instance, …..

[10] While our benchmark measure of losses due to natural disasters are the monetary losses just described, one should note that we also experiment with using deaths as a proxy; see the end of Section 4.

a measure of geographical size of each country is taken from the Global Rural-Urban Mapping Project (GRUMP).

3.5 Sample

Although in principle the data required for our estimation could start from 1960, one should note that we restrict our sample to cover the period 1980-2004.[11] This is done for two reasons. Firstly, while for some of the underlying disaster types the hazard indicators are derived from time invariant and/or data over long time periods, for others this would have been constructed from data available from roughly the 1980s onwards. If the local probabilities of occurrence along the complete range of intensities of these disasters vary over time then our proxy may not be representative of the actual distributions for the period prior to 1980. Secondly, there may be some concern that particularly for earlier years the quality of the EM-DAT database may have been poor.[12] Restricting our sample period to observations from 1980 onwards and using only observations where the non-missing values on all variables used in our analysis resulted in a total sample size of 4,144 covering 181 countries. A set of summary statistics for all variables is provided in Table.

Section : Econometric Analysis

Our primary empirical purpose is to investigate whether the data is consistent with the predictions from our theoretical framework. In this regard we start off with the base specification relating economic losses to level of economic development:

[11] One should note, however, that including the earlier data in our analysis did not change the results qualitatively and little quantitatively.

[12] There are suspiciously less disasters recorded in the database for very early years.

$$\log\left(\frac{LOSSES_{i,t}}{POP_{i,t-1}}+1\right)=\alpha+\beta_1\log\left(\frac{GDP_{i,t-1}}{POP_{i,t-1}}\right)+\beta_2\log\left(\frac{GDP_{i,t-1}}{POP_{i,t-1}}\right)^2+\lambda_j\sum_{j=1}^{m}X_{i,t-1}+\varepsilon_{i,t} \quad (13)$$

where *i* is a country level and *t* a time subscript, $\frac{LOSSES_{i,t}}{POP_{i,t-1}}$ are a (per capita) measure of economic losses due to natural disasters as taken from the EM-DAT database, $\log\left(\frac{GDP_{i,t-1}}{POP_{i,t-1}}\right)$ is a measure of economic development (wealth) as taken from the World Penn Tables and included both in levels and in quadratic form to capture its arguably non-linear relationship to losses, $\sum_{j=1}^{m}X_{i,t-1}$ is a set of other possibly time and/or cross-country varying control variables, and ε is an error term. In terms of other control variables we as a start include the logged value of national population density and the logged value of the total geographical area of a country, as well as a set of year dummies.

One should note that the dependent variable in (13) consists of a large number of zeros since many countries for many years experience no economic losses, which may be due to no disasters occurring in that year or potential disasters not translating into economic losses. This renders standard Ordinary Least Squares inappropriate as an estimation methodology and we hence resort to using tobit estimator which explicitly deals with such lower truncation in the data. To take account of potential heteroskedasticity and correlation of observations across time within countries, we calculate robust standard errors allowing for within country clustering of the error term.

The estimates of our base specification in (13) are given in Table 2. As can be seen, the significant coefficients on *log(AREA$_i$)* and *log(POP$_{i,t-1}$/AREA$_i$)* indicate that per capita economic losses due to disasters increase with geographical size and greater population density of a country. More importantly, both GDP per capita and its squared value are found to be statistically significant. The signs of their coefficients suggest an inverted us-shaped relationship between economic losses and economic development. Calculations using the estimated coefficients indicate that the turning point occurs at a point slightly above the mean level of GDP per capita (at a logged GDP per capita value of 9.48), - which corresponds roughly to the wealth of a country like Chile - after which the level of development and economic losses have a negative relationship.

We next include our measure of natural disaster multi-hazard measure in (13), denoted as *HZ*, shown in the second column of Table 3. Accordingly, its inclusion first of all noticeably changes the size of the coefficients on our indicator of development and its value squared. This demonstrates that not controlling for differences in hazard will bias the estimated economic loss – development relationship. Under these new coefficients the turning point is predicted to be later (at a logged GDP per capita value of 10), i.e., around the level of development of New Zealand. Our country level proxy of risk exposure is found to have a significant positive effect on economic losses suffered. In other words, unsurprisingly given that we have no indicactor of the potential degree of a disaster, countries with a higher probability of a natural disaster are more likely to suffer greater costs due to disasters.

In the third column of Table 3 we interact our hazard proxy with GDP per capita in levels and its squared term. As can be seen, both the slope of the wealth-development link as well as its rate of change significantly depend on the probability of a natural hazard of a country. More specifically, the signs on the interaction terms indicate that the more hazardous a country, the flatter its inverted u-shaped relationship will be. In other words for countries where natural disasters are more likely, greater wealth will have a reducing effect on economic losses suffered at a later stage of development and at a lower rate. In Figure 3 we depict the implied wealth-loss relationship for when the hazard is at the 0th and at the 20th, 40th, 60th, and 80th percentile of the non-zero distribution in our data. As can be seen, the zero, 20th, 40th, and 60th percentile curves are all inverted u-curves, while at the 80th percentile the shape is reversed. As a matter fact, simple calculations show that this 'reversal' occurs around the 70th percentile.

We also conduct a number of robustness checks. Firstly, as pointed out earlier, the distribution of our multi-hazard hazard index is extremely skewed where the value for some countries is multifold of the average. Feasibly these extreme outliers could be driving our results. To investigate this we re-ran the specification in the third column but excluding all countries for which the hazard rate was above the 90th percentile of its distribution, i.e., above values of 45. As can be seen, not only are the results qualitatively, but also quantitatively very similar to before.

One may also want to note that although the economic loss data is the most comprehensive collection of information on costs of natural disasters across countries over time available, it has some shortcomings. [13] First of all, the data on damages suffered due to the natural disasters generally includes only direct, and not indirect, costs. Additionally, there is the possibility that reported damages may be exaggerated in order to secure greater international assistance. Finally, there may be some suspicion that data may be of poorer

[13] See Toya and Skidmore (2007).

quality in developing countries, since these tend to have less insurance coverage, poorer bookkeeping, and more informal markets. As an alternative measure we thus also experiment with the (logged) number of deaths per capita, also given in the EM-DAT database, under the assumption that human losses are likely to be correlated with actual monetary losses.[14] The results of using this alternative dependent variable in our specification with all interaction terms are given in the fifth column of Table 3. Reassuringly, one finds qualitatively similar coefficients as for the economic loss data.

Thus far we have treated all six disasters as one homogenous group in using a mult-hazard index in our analysis. Feasibly, however, disasters may have very different effects on the wealth-loss relationship. Moreover, as discussed above, the underlying hazard measures come from very different data sources, some based on actual events (windstorms, floods, volcanoes, droughts), some on time invariant probabilistic measures (landslides), and others on both (earthquakes). Additionally, these data sources differ in their quality.[15] To investigate whether our general results hold across disasters types we calculated analogous country level measures of hazards for each disaster type (i.e., by not summing across hazards). Redefining the dependent variable to only consider losses of the disaster type in question, we first re-ran our specification including the relevant hazard measure in Table 4. Accordingly, for all disaster types the hazard measure has a positive and significant effect on losses, hence providing some support that these are appropriate proxies of the probability of a disaster occurring along the

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[14] The correlation between the reported number of deaths and the reported number of losses was found to be positive and statistically significant.

[15] For example, the flood data is known to be poor for parts of the 1990's. There is also some suspicion that the cyclone data may differ in quality across regions. Finally, although there is something to be said for using a uniform definition of drought, such as the weighted anamoly of standard precipitation, there is some skepticism in the literature whether a single measure can be appropriate for all regions of the globe; see, for instance, Bhalme and Mooley (1979).

range of severities. One may want to note in this regard that in this base specification, however, for both windstorms and landslides there appears to be no relationship between losses and economic development.[16]

We next generated and included the necessary interaction terms to replicate the specification from the third column in Table 3 for each disaster type. The results of this are given in Table 5. Firstly, one may want to note that there is now a significant wealth-loss relationship for all disaster types, although not always non-linear. Moreover, in terms of our interaction terms for three of the six disaster types, namely, windstorms, earthquakes, and landslides, we get similar qualitative results to our mults-hazard regression, except that for windstorms the lack of significance on the squared logged GDP per capita terms indicates that any non-linear effect of wealth on losses only acts through reducing the dampening effect of being subjected to a greater probability of windstorms. In contrast, being more hazardous in terms of droughts, floods, or volcanoes, does not appear to influence how greater development affects economic losses.

We also experimented with using our alternative proxy for losses, i.e., the logged deaths per capita, for the different disaster types, as shown in Table 6. Here one discovers that the results derived from the multi-hazard analysis holds across four different disaster types, namely windstorms, earthquakes, droughts, and landslides. In contrast this is not the case for floods and volcanoes. One may want to note that the data underlying the hazard calculation is particularly poor for flood events.[17]

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[16] This holds even when we exclude the squared term of logged GDP per capita.
[17] See Diley et al (2005).

Given that our analysis by disaster types consistently showed a lack of results in congruence with our multi-hazard analysis for floods and volcanoes we re-conducted our multi-hazard analysis excluding these two disaster types. The results of this are given the final column of Table 3. Reassuringly, only considering windstorms, earthquakes, droughts, and landslides does not alter our overall conclusions regarding the interplay between economic losses, the level of development, and risk exposure, although this does alter the size of these effects marginally.

Another concern may be with regard to the nature our sample. More specifically, by creating a panel of country loss data over time we are not only including years in which potential natural disasters translated into actual natural disasters and years in which potential natural disaster events did not cause enough damage to be considered a 'disaster', but also years in which neither such events took place. Moreover, we do not control for the scientific severity of the event when it did occur. If either the probability of a potential disaster event or the magnitude of the event are correlated with wealth, but not completely captured by our hazard variable, then our results may be biased. Of course, identifying potential disaster events and their magnitude would be a difficult, if not impossible, task for all disaster types included in our data. One exception in this regard are earthquakes, for which there are relatively accurate historical records to identify actual significant earthquake events, even if they did not translate into major natural disasters as captured by the EM-Dat database. In particular, the Significant Earthquakes Database maintained by the NOAA contains a listing of earthquakes over time if they resulted in ten or more deaths, moderate damage (approximately $1 million or more), magnitude of at least 7.5 on the Richter Scale, or a Modified Mercalli Intensity of at least X .

Additionally, the database includes a scientific measure of the actual magnitude of the earthquake in terms of its Richter scale.

To investigate whether the concerns regarding our sample and the lack of a measure of the intensity of events we reduced all earthquake event country observations in the Significant Earthquakes Database and re-ran (13) including the hazard interaction terms as well as a measure of the energy released as implied by the magnitude, where we weight the latter by the share of population within a country within 50km of the epicenter.[18] One should note that this reduced our sample to 93 data points, of which 59 were earthquake event years that did not, according to the EM-DAT database, result in economic losses. The results are given in the last column of Table 4. As can be seen, the energy of the earthquake, as would be expected, is positively related to the amount of economic losses. More importantly, our results concerning the loss-wealth relationship and the dependency of this on the hazard faced by a country, shown in the last column of Table 5, are qualitatively similar as in Column 6 of the same table, where we used our benchmark sample for earthquakes.

Finally, one should note that our results stand in stark contrast to those by Toya and Skidmore (2007) and Kahn (2005) - who also avail of the EM-DAT database - in that we find a non-linear, i.e., a bell-shaped relationship between income and natural disaster losses even if we do not control for expected risk, thus suggesting that their analyses possibly suffered from misspecification. In order to verify that this contrast in results is not a matter of our different econometric methodology or our sample we thus also implemented their approaches on our data set. In particular, we first follow Toya and Skidmore (2007) by reducing the observations

[18] Energy released is measured in joules (divided by 10^{17}) as given by the scale at http://earthquake.usgs.gov/learning/faq.php?categoryID=2&faqID=33.

to those where the number of deaths was positive and then defining the dependent variable as the log of the number of deaths. We then regressed this variable on the log of GDP per capita, the log of area and the log of population, as shown in the first column of Table 6. As can be seen, similar to Toya and Skidmore (2007) we discover a negative and significant coefficient on the log of GDP per capita, suggesting that losses fall with wealth. In the second column we then included the squared value of the log of GDP per capita. Importantly one now finds a bell shaped relationship between losses and wealth, as suggested by our model. The inclusion of HZ, as shown in the subsequent column, indicates that more hazardous countries experience greater losses. Moreover, the interaction terms of this variable with the GDP per capita terms in the fourth column show that the wealth income relationship crucially depends on the hazard faced by a county, as we already found above.

We next implemented a zero inflated negative binomial model using the count of deaths as the dependent variable, as in Kahn (2005), on our data. The results of the negative binomial regression of this model are shown in the last four columns of Table 6.[19] Accordingly, as Kahn (2005) found with his data set, when only including the level of the log of GDP per capita, the results suggest that losses and wealth are negatively related. Once one includes the squared value of wealth, however, one gets a similar non-linear results as we found above in our specification. Moreover, as shown in the final column, this non-linearity depends on the risk exposure level of a country.

[19] The zero inflated negative binomial regressions consists of a logit model of the probability that zero deaths, as well as a negative binomial regression predicting the death count. For the former we used the same explanatory variables and, as Kahn (2005), the sum of total deaths for each country. Here we report, however, only the results of the negative binomial regression, detailed results of the logit regression are available from the authors upon request.

5. Conclusion

In this article we investigate the relationship between the losses from natural disasters, the exposure to different levels of natural hazard risk (risk exposure) and the stages of economic development. Our main contributions are the analysis of this relationship via a theoretical model as well as through an econometric analysis of a cross country panel dataset. We find that both the theoretical model and the empirical analysis predict a non-linear relationship between economic losses and the stages of economic development that crucially depends on country's risk exposure to natural disasters. More specifically, countries that face a low or intermediate risk exposure have a bell-shaped relationship between economic losses and wealth; whereas countries that face a high risk exposure have a u-shaped relationship between losses and wealth. This stands in contrast to the current literature, which solely suggests decreasing losses with increasing wealth.

Our results indicate that extreme care must be taken when modeling and analyzing the relationship between wealth and economic development. More specifically, there appears to be no simple 'increasing wealth – reducing losses' relationship, making policy recommendations that much harder. One primary prominent feature that comes out of our analysis is, however, that the exposure to natural disaster risk is an important driving force behind any relationship between economic losses and wealth. In terms of policy suggestions, it seems therefore essential to generate and provide as much information as possible concerning likely current and future risk exposures of the different areas where people are living or planning to move to. This information is necessary for agents to properly adapt to the natural hazard situation and should therefore prevent excessive losses.

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Table 2: Summary Statistics

Variable	Mean	St. Dev.
$LOSS_{all}$	0.442637	1.198036
$\log(GDP/POP_{i,t-1})$	8.303593	1.13478
HZ	22.71573	33.6286
$\log(POP/AREA_{i,t-1})$	-3.02509	1.587856
$\mathrm{Log}(AREA_{I})$	11.44056	2.584813
$LOSS_{EQ}$	0.057564	0.454302
$LOSS_{LS}$	0.007359	0.150434
$LOSS_{CY}$	0.213984	0.911184
$LOSS_{FL}$	0.157363	0.626108
$LOSS_{DR}$	0.042535	0.383609
$LOSS_{VO}$	0.005302	0.130794
$DEATH_{EQ}$	0.005335	0.0596863
$DEATH_{EQ}$	0.001828	0.040488
$DEATH_{LS}$	0.00035	0.009327
$DEATH_{CY}$	0.001874	0.029065
$DEATH_{FL}$	0.001029	0.013799
$DEATH_{DR}$	0.001869	0.056977
$DEATH_{VO}$	0.000138	0.007362
$ENERGY$	0.340081	1.512644

Notes: (1) Summary statics for regression sample only; (2) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes.
(3) ENERGY is multiplied by 10^{14}.

Table 3: Multi-Hazard Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*DEATH*	*LOSS*
log(GDP/POP$_{i,t-1}$)	7.043***	5.312***	7.381***	7.071***	0.141**	8.467***
	(2.110)	(1.952)	(2.382)	(2.633)	(0.055)	(3.021)
[log(GDP/POP$_{i,t-1}$)]^2	-0.367***	-0.258**	-0.396***	-0.374**	-0.009***	-0.432**
	(0.126)	(0.118)	(0.142)	(0.158)	(0.003)	(0.180)
HZ$_i$		0.023***	0.745**	0.848**	0.010*	1.139***
		(0.006)	(0.334)	(0.421)	(0.006)	(0.437)
log(GDP/POP$_{i,t-1}$)*HZ$_i$			-0.191**	-0.208**	-0.003*	-0.281***
			(0.078)	(0.102)	(0.001)	(0.102)
[log(GDP/POP$_{i,t-1}$)]^2*HZ$_i$			0.013***	0.013**	0.000**	0.018***
			(0.005)	(0.006)	(0.000)	(0.006)
log(POP/AREA$_{i,t-1}$)	0.841***	1.028***	1.051***	1.038***	0.030***	1.139***
	(0.119)	(0.126)	(0.126)	(0.129)	(0.007)	(0.165)
Log(AREA$_I$)	0.686***	0.768***	0.768***	0.727***	0.027***	0.786***
	(0.061)	(0.059)	(0.059)	(0.063)	(0.006)	(0.081)
Constant	-42.211***	-36.463***	-43.883***	-42.604***	-0.910***	-51.820***
	(8.716)	(7.984)	(9.822)	(10.799)	(0.240)	(12.353)
SAMPLE:	ALL	ALL	ALL	HZ$_i$<45	ALL	CY,DR,EQ,LS
Observations	4144	4144	4144	3685	4144	4144
Left Cens.	3136	3136	3136	2783	2766	3466
Pseudo R2	0.0720	0.0839	0.0901	0.103	5.925	0.0787

Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10 per cent significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes.

Table 4: Single Hazard Regressions – No Interaction Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*
log(GDP/POP$_{i,t-1}$)	3.426	8.401**	4.654	3.138**	11.345**	8.568**	8.900***
	(3.116)	(4.130)	(3.441)	(1.235)	(5.454)	(3.841)	(0.017)
[log(GDP/POP$_{i,t-1}$)]^2	-0.125	-0.457*	-0.230	-0.159**	-0.638**	-0.456**	-0.458***
	(0.187)	(0.241)	(0.208)	(0.074)	(0.317)	(0.223)	(0.002)
HZ$_i$	0.063***	0.032*	0.089**	0.052***	0.516**	0.070***	0.123***
	(0.014)	(0.017)	(0.042)	(0.012)	(0.205)	(0.016)	(0.005)
ENERGY							0.317***
							(0.013)
log(POP/AREA$_{i,t-1}$)	1.165***	0.805***	0.861***	0.837***	0.656**	1.370***	0.139***
	(0.207)	(0.220)	(0.249)	(0.097)	(0.297)	(0.256)	(0.037)
Log(AREA$_I$)	0.735***	1.071***	0.803***	0.824***	0.888***	1.370***	0.611***
	(0.098)	(0.145)	(0.179)	(0.063)	(0.230)	(0.185)	(0.010)
Constant	-31.941**	-61.575***	-37.860***	-27.270***	-68.965***	-59.855***	-59.663***
	(12.749)	(17.775)	(14.076)	(5.374)	(25.503)	(16.926)	(0.140)
SAMPLE:	CY	DR	SL	FL	VO	EQ	EQ
Observations	4144	4144	4144	4144	4144	4144	93
Left Cens.	3649	4045	4107	3602	4126	3987	59
Pseudo R2	0.0869	0.0998	0.124	0.153	0.109	0.179	0.246

Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10 per cent significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes. (6) ENERGY is multiplied by 10^{14}.

Table 5: Single Hazard Regressions – Interaction Effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*
log(GDP/POP$_{i,t-1}$)	5.950*	8.627*	6.429*	3.016*	12.776**	10.357**	19.231***
	(3.254)	(4.745)	(3.487)	(1.602)	(5.233)	(4.097)	(6.522)
[log(GDP/POP$_{i,t-1}$)]^2	-0.276	-0.489*	-0.336	-0.158	-0.721**	-0.566**	-1.061***
	(0.196)	(0.276)	(0.212)	(0.097)	(0.304)	(0.239)	(0.377)
HZ$_i$	2.106***	1.465	15.987***	0.116	55.856	3.278*	5.657***
	(0.566)	(1.308)	(5.777)	(0.530)	(42.528)	(1.940)	(1.833)
log(GDP/POP$_{i,t-1}$)*HZ$_i$	-0.501***	-0.406	-3.809***	-0.028	-12.871	-0.792*	-1.335***
	(0.140)	(0.331)	(1.371)	(0.129)	(10.048)	(0.458)	(0.422)
[log(GDP/POP$_{i,t-1}$)]^2*HZ$_i$	0.031***	0.028	0.227***	0.002	0.745	0.049*	0.080***
	(0.009)	(0.021)	(0.081)	(0.008)	(0.592)	(0.027)	(0.024)
ENERGY	---	---	---	---	---	---	0.356**
							(0.168)
log(POP/AREA$_{i,t-1}$)	1.152***	0.799***	0.904***	0.830***	0.663**	1.427***	0.252
	(0.212)	(0.209)	(0.240)	(0.098)	(0.300)	(0.260)	(0.301)
Log(AREA$_i$)	0.739***	1.060***	0.832***	0.813***	0.891***	1.393***	0.622**
	(0.102)	(0.138)	(0.183)	(0.064)	(0.233)	(0.191)	(0.282)
Constant	-42.401***	-61.014***	-45.399***	-26.279***	-75.136***	-67.103***	-93.942***
	(13.219)	(20.251)	(14.335)	(6.592)	(24.633)	(17.981)	(29.505)
SAMPLE:	CY	DR	SL	FL	VO	EQ	EQ
Observations	4144	4144	4144	4144	4144	4144	93
Left Cens.	3649	4045	4107	3602	4126	3987	59
Pseudo R2	0.0926	0.104	0.136	0.154	0.113	0.186	0.262

Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10 per cent significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes. (6) ENERGY is multiplied by 10^{14}.

Table 6: Single Hazard Regressions – Alternative Loss Indicator

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	*DEATH*	*DEATH*	*DEATH*	*DEATH*	*DEATH*	*DEATH*
log(GDP/POP$_{i,t-1}$)	0.147**	0.286***	2.678*	0.037**	0.033	1.381*
	(0.059)	(0.105)	(1.489)	(0.015)	(0.023)	(0.823)
[log(GDP/POP$_{i,t-1}$)]^2	-0.008**	-0.017***	-0.198**	-0.002**	-0.002	-0.081*
	(0.003)	(0.006)	(0.099)	(0.001)	(0.001)	(0.048)
log(POP/AREA$_{i,t-1}$)	0.026***	0.023***	0.160***	0.004***	0.011***	0.041*
	(0.008)	(0.006)	(0.062)	(0.001)	(0.004)	(0.022)
Log(AREA$_{I}$)	0.018***	0.025***	0.191***	0.005***	0.011***	0.060*
	(0.005)	(0.007)	(0.071)	(0.001)	(0.004)	(0.031)
HZ$_i$	0.023**	0.083*	0.413*	0.079**	-0.003	5.247
	(0.010)	(0.049)	(0.224)	(0.033)	(0.005)	(3.877)
log(GDP/POP$_{i,t-1}$)*HZ$_i$	-0.005**	-0.020*	-0.110*	-0.019**	0.001	-1.238
	(0.002)	(0.011)	(0.058)	(0.008)	(0.001)	(0.922)
[log(GDP/POP$_{i,t-1}$)]^2*HZ$_i$	0.000**	0.001*	0.007**	0.001**	-0.000	0.073
	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.055)
Constant	-0.909***	-1.543***	-12.709**	-0.221***	-0.287**	-6.901*
	(0.299)	(0.513)	(5.895)	(0.077)	(0.133)	(3.990)
SAMPLE:	CY	EQ	DR	SL	FL	VO
Observations	4144	4144	4144	4144	4144	4144
Left Cens.	3503	3872	4108	3911	3263	4121
Pseudo R2	0.963	0.903	0.191	-1.812	-0.635	0.482

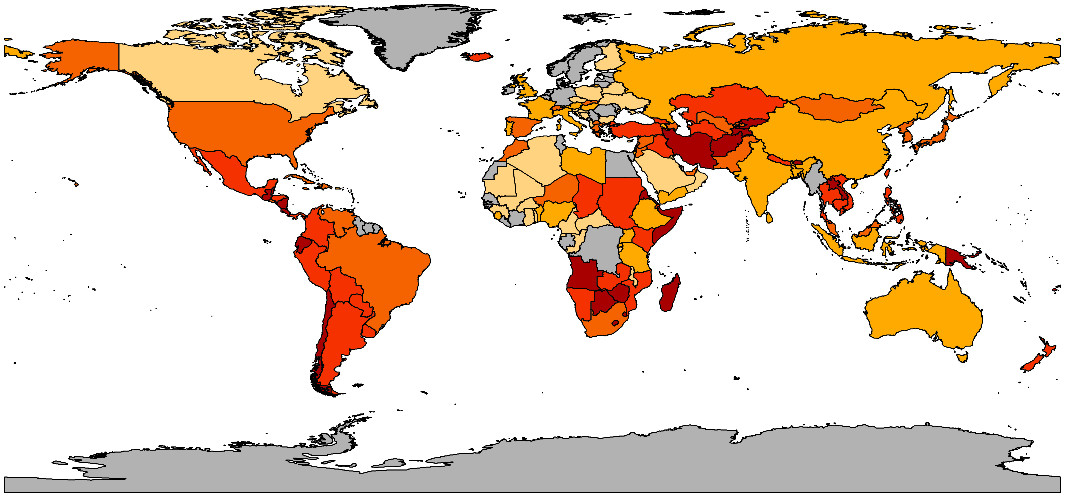
Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10 per cent significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes.

Table 7: Replicating Kahn (2005) and Toya and Skidmore (2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	*DEATH*	*DEATH*	*DEATH*	*DEATH*	*DEATH*	*DEATH*	*DEATH*	*DEATH*
log(GDP/POP$_{i,t-1}$)	-0.524***	3.176***	2.561***	3.658***	-0.844***	4.091***	4.270***	7.347***
	(0.043)	(0.688)	(0.681)	(0.916)	(0.066)	(0.775)	(0.773)	(1.195)
[log(GDP/POP$_{i,t-1}$)]^2		-0.221***	-0.182***	-0.252***		-0.290***	-0.294***	-0.487***
		(0.041)	(0.040)	(0.054)		(0.046)	(0.045)	(0.071)
log(POP/AREA$_{i,t-1}$)	-0.229***	-0.219***	-0.117***	-0.117***	0.757***	0.784***	0.899***	0.900***
	(0.038)	(0.036)	(0.039)	(0.039)	(0.045)	(0.044)	(0.045)	(0.045)
log(AREA$_{I}$)	-0.369***	-0.358***	-0.300***	-0.304***	0.676***	0.698***	0.744***	0.730***
	(0.026)	(0.026)	(0.027)	(0.027)	(0.028)	(0.028)	(0.028)	(0.029)
HZ$_i$			0.011***	0.288**			0.016***	0.599***
			(0.002)	(0.124)			(0.003)	(0.157)
log(GDP/POP$_{i,t-1}$)*HZ$_i$				-0.072**				-0.152***
				(0.030)				(0.040)
[log(GDP/POP$_{i,t-1}$)]^2*HZ$_i$				0.005**				0.010***
				(0.002)				(0.003)
Constant	2.969***	-12.440***	-10.760***	-14.975***	4.760***	4.721***	4.387***	4.432***
	(0.500)	(2.926)	(2.875)	(3.881)	(0.744)	(0.744)	(0.528)	(0.506)
SAMPLE:	DEATH>0	DEATH>0	DEATH>0	DEATH>0	ALL	ALL	ALL	ALL
METHOD:	OLS	OLS	OLS	OLS				
Observations	1330	1330	1330	1330	4144	4144	4144	4144
(Pseudo) R2								

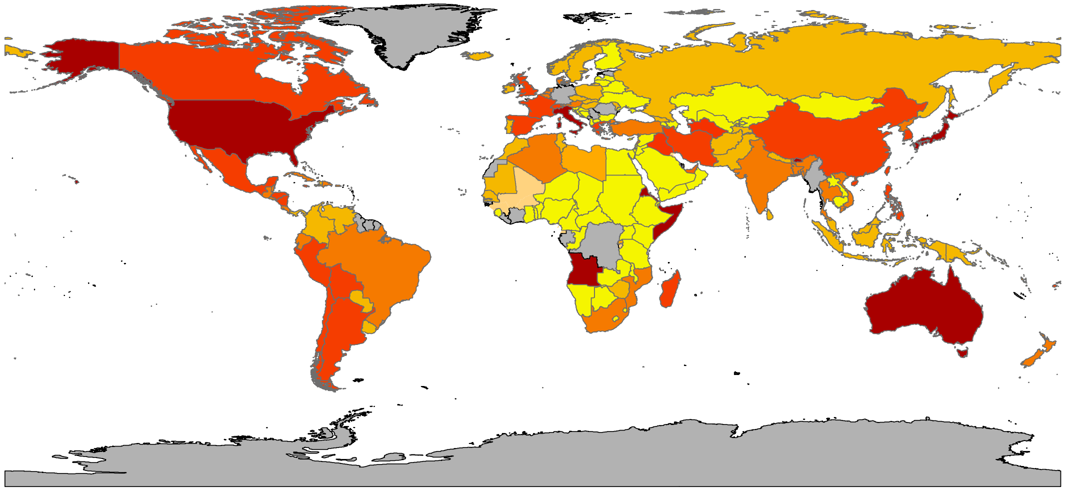
Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10 per cent significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes.

Figure 1: Distribution of HZ



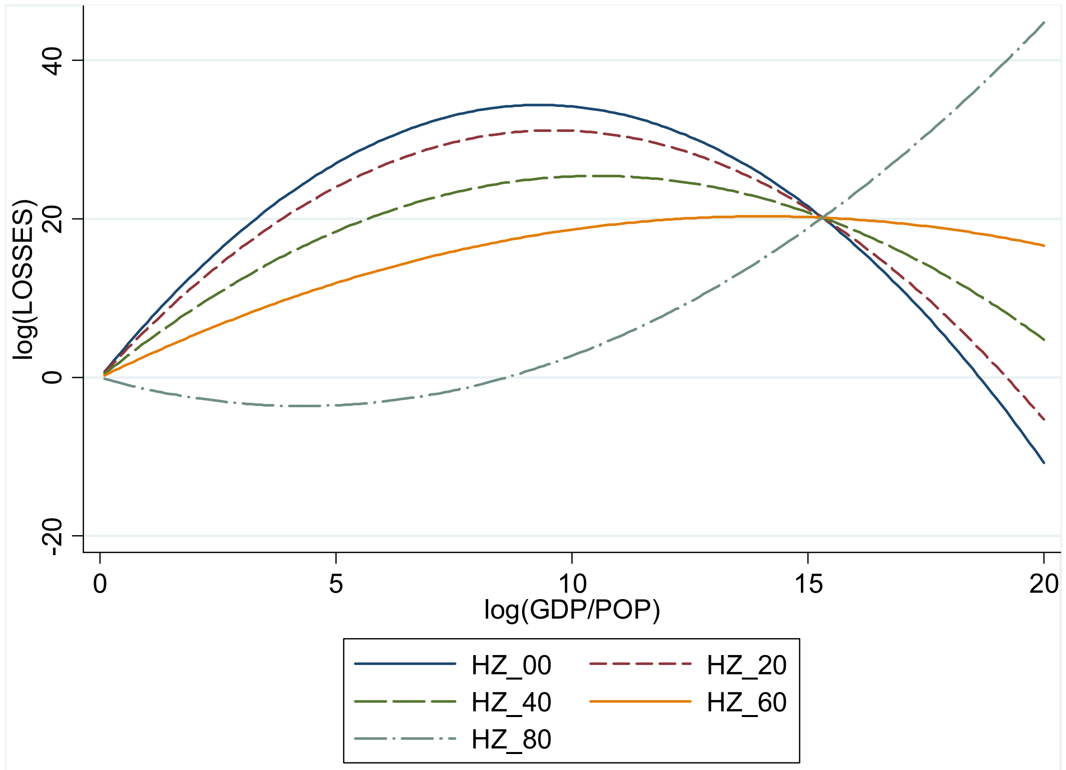
Note: (1) Grey coloured areas indicate zero value. (2) Darker shading of non-grey coloured countries indicate greater value of HZ.

Figure 2: Distribution of LOSS



Note: (1) Grey coloured areas indicate zero value. (2) Darker shading of non-grey coloured countries indicate greater value of per capita losses.

Figure 3: The Losses-Wealth Relationship by Natural Disaster Hazard Level



Data Appendix*: Outline of the Construction of a Multi-Hazard Risk Exposure Index by Dilley et al (2005)*

First, using the spatial grid schemata from the Gridded Population of the World (GPW) version 1 data set, the globe was divided into 2.5' x 2.5' spatial units, resulting in about 8.7 million cells. Grid cells with less than five persons per kilometer were masked out since, while residents might be exposed to natural disasters, total casualties and/or losses are likely to be small. For the remaining cells indicators of hazard were then calculated separately for cyclones, droughts, earthquakes, floods, landslides, and volcanoes given available spatial data on probability, occurrence, and extent:

- *Cyclones*: For cyclones storm track data covering the Atlantic, Pacific, and Indian Oceans over the period 1980-2000 was used in conjunction with a wind field model to calculate the wind speeds experienced within each grid cell. A measure of local hazard then consisted of considering the frequency as well as the wind strength of events.
- *Droughts*: To calculate local measures of the hazard of droughts the weighted anamoly of standardized precipitation were computed for each grid cell from monthly rainfall data over the 21 year period. Drought events, from which the local hazard was constructed, were identified when a cell experienced a precipitation deficit was less than or equal to 50 per cent of its long term median value for three or more consecutive months.
- *Earthquakes*: For earthquakes information from both the local probabilistic estimate from the Global Seismic Hazard Program as well as actual earthquake events for the period 1976 to 2000 were utilized.
- *Floods*: Flood hazards measures were derived from the Dartmouth Flood Observatory database which provides information on the location and extent of major flood events across the globe since 1985.
- *Landslides*: As a measure of the probability of landslide disasters information was taken from the global landslide hazard map developed by the Norwegian Geotechnical Institute which is based on local slope, soil and soil moisture conditions, precipitation, seismicity, and temperature.
- *Volcanoes*: For volcanoes spatial coverage of volcanic activity from 79 A.D. through 2000 A.D from the Worldwide Volcano Database served as the basis for the local hazard measure construction.

In order to arrive at a local summary measure of hazard for each disaster type each grid cell was grouped into global deciles according to the local hazard derived from the underlying data just described.[20] Each cell was then for each disaster type category weighted according to its decile in the global distribution on a 1 to 10 scale, where those in the top decile were given a value of 10, those in the second highest a value of 9 etc. Values of 8 and above were then summed over all disaster types to arrive at a multi-hazard summary measure at the grid cell level, necessarily ranging between 0 and 48.

[20] For example, for cyclones the local hazard would have been calculated by translating wind speeds at the one square kilometer scale into the Saffir Simpson Hurricane scale, and using these to calculate how often a grid cell is hit and what severity over the 21 year period.

Since the probability of total losses due to natural disasters will not only depend on the probability and scale of the incident but also on the potential local exposure, we follow the Diley et al (2005) and for each grid cell multiply the multi-hazard summary measure by their proposed index of local population density estimate based on the 2000 values from GPW data, which similarly consists of values ranging from 1 to 10 according to its global decile grouping. Thus this population density weighted multi-hazard index can feasibly range in value from 0 to 480.